Proc. Digital del Continguts Musicals

Session 1:
Pattern Recognition

1. **Music Content Analysis**
2. **Pattern Classification**
3. **The Statistical Approach**
4. **Distribution Models**
5. **Singing Detection**

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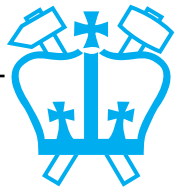
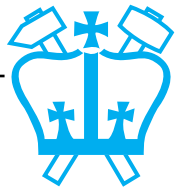
Spring 2003

1 Music Content Analysis

- **Music contains information at many levels**
  - what is it?
- **We'd like to get this information out automatically**
  - fine-level transcription of events
  - broad-level classification of pieces
- **Information extraction can be framed as: pattern classification / recognition or machine learning**
  - build systems based on (labeled) training data



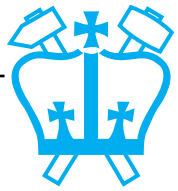


Music analysis

- **What might we want to get out of music?**
- **Instrument identification**
  - different levels of specificity
  - ‘registers’ within instruments
- **Score recovery**
  - transcribe the note sequence
  - extract the ‘performance’
- **Ensemble performance**
  - ‘gestalts’: chords, tone colors
- **Broader timescales**
  - phrasing & musical structure
  - artist / genre clustering and classification

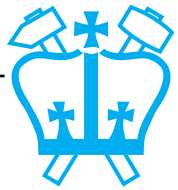
Course Outline

- **Session 1: Pattern Classification**
  - MLP Neural Networks
  - GMM distribution models
  - Singing detection
- **Session 2: Sequence Recognition**
  - The Hidden Markov Model
  - Chord sequence recognition
- **Session 3: Musical Applications**
  - Note transcription
  - Music summarization
  - Music Information Retrieval
  - Similarity browsing



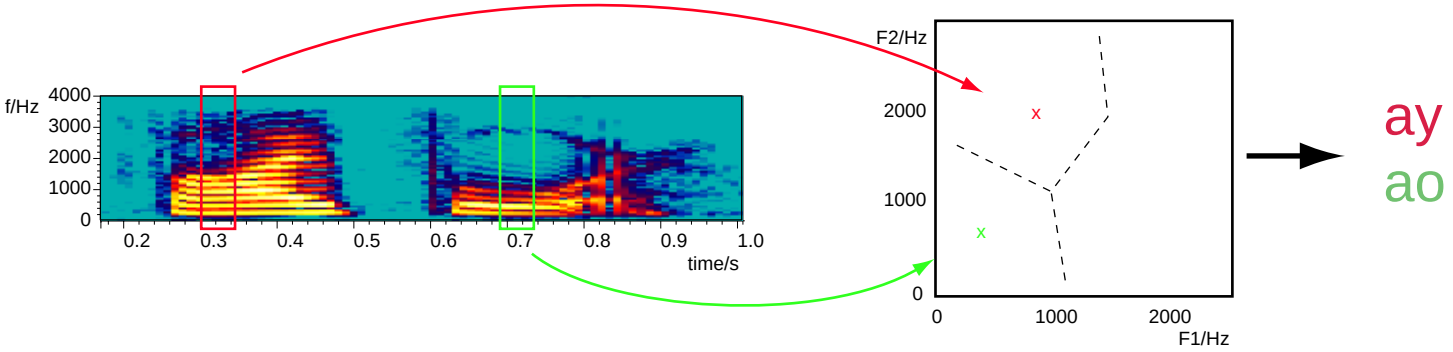
Outline

1. Music Content Analysis
2. **Pattern Classification**
   - classification
   - decision boundaries
   - neural networks
3. The Statistical Approach
4. Distribution Models
5. Singing Detection

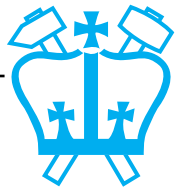


2 Pattern Classification

- **Classification means:**
  finding categorical (*discrete*) labels
  for real-world (*continuous*) observations

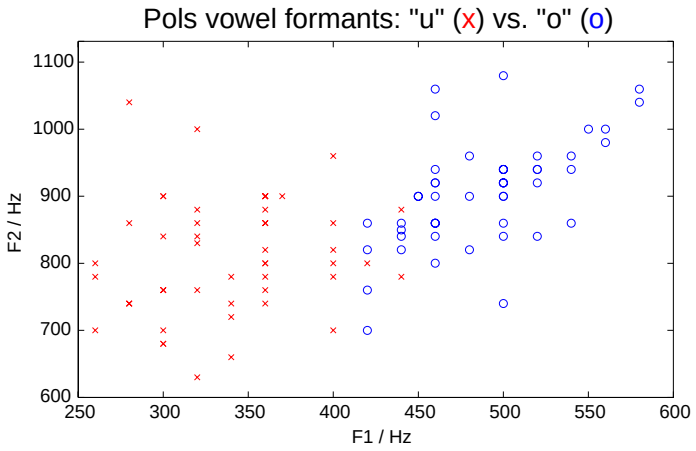


- **Why?**
  - information extraction
  - conditional processing
  - detect exceptions

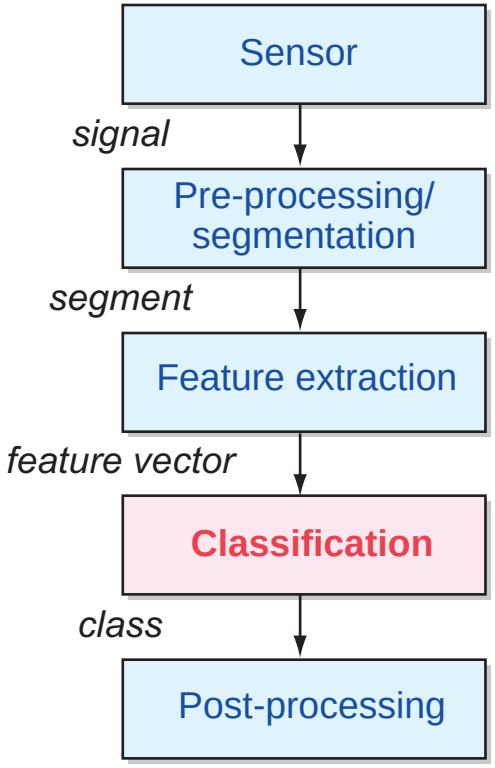


Building a classifier

- **Define classes/attributes**
  - could state explicit rules
  - better to define through ‘training’ examples
- **Define feature space**
- **Define decision algorithm**
  - set parameters from examples
- **Measure performance**
  - calculate (weighted) error rate



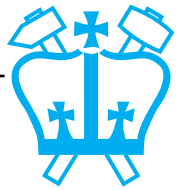
Classification system parts



- STFT
- Locate vowels

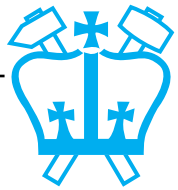
- Formant extraction

- Context constraints
- Costs/risk

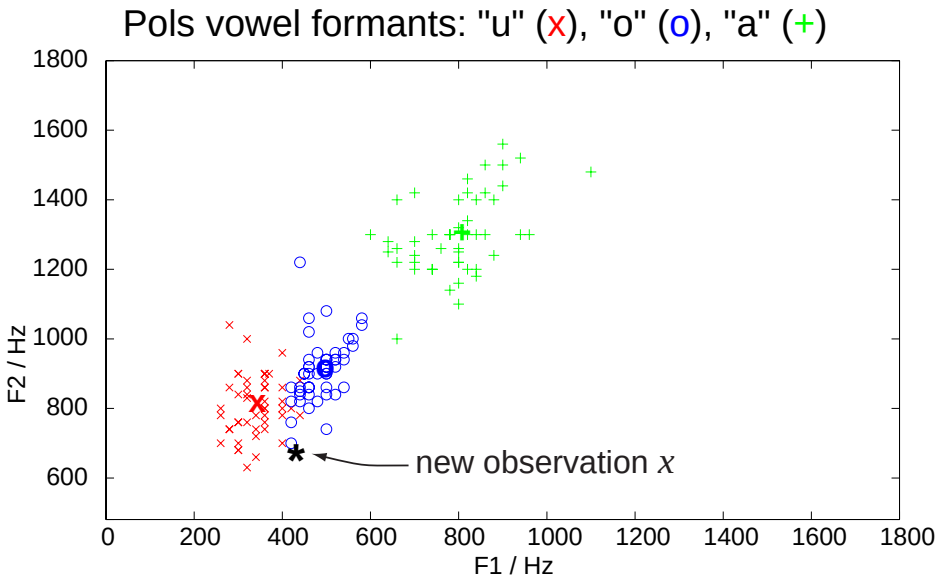


Feature extraction

- **Right features are critical**
  - waveform vs. formants vs. cepstra
  - *invariance* under irrelevant modifications
- **Theoretically equivalent features may act very differently in practice**
  - representations make important aspects explicit
  - remove irrelevant information
- **Feature design incorporates 'domain knowledge'**
  - more data → less need for 'cleverness'?
- **Smaller 'feature space' (fewer dimensions)**
  → simpler models (fewer parameters)
  → less training data needed
  → faster training



Minimum distance classification



- **Find closest match (nearest neighbor)**

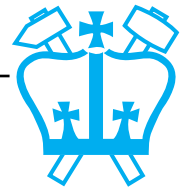
  $min[D(x, y_{\omega,\, i})]$

  - choice of distance metric $D(x,y)$ is important

- **Find representative match (class prototypes)**

  $min[D(x, z_{\omega})]$

  - class data $\{y_{\omega,i}\} \rightarrow$ class *model* z_{ω}



Linear classifiers

- **Minimum Euclidean distance is equivalent to a linear discriminant function:**
  - examples $\{ y_{\omega,i} \} \rightarrow$ template $z_\omega = \text{mean}\{ y_{\omega,i} \}$
  - observed feature vector $x = [x_1\ x_2\ \ldots]^T$
  - Euclidean distance metric

$$D[x, y] = \sqrt{(x-y)^T (x-y)}$$

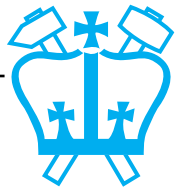
  - minimum distance rule:

$$\text{class } i = \underset{i}{\text{argmin}}\ D[x, z_i]$$

$$= \underset{i}{\text{argmin}}\ D^2[x, z_i]$$

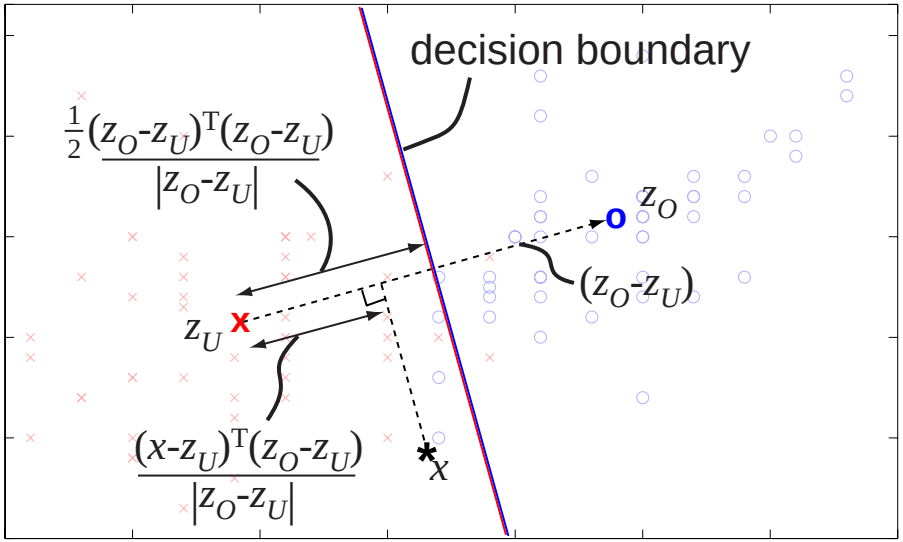
  - i.e. choose class O over U if

$$D^2[x, z_O] < D^2[x, z_U] \quad \ldots$$

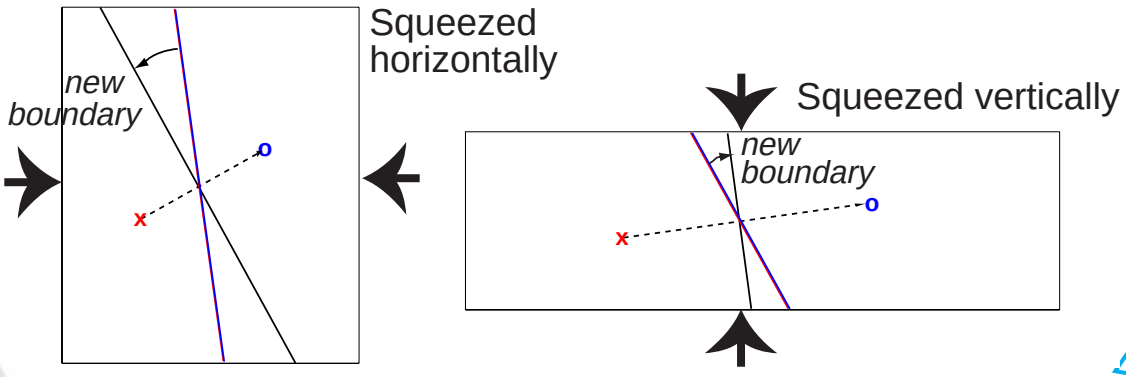


Linear classification boundaries

- **Min-distance divides normal to class centers:**

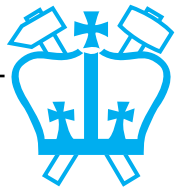


- **Scaling axes changes boundary:**



Decision boundaries

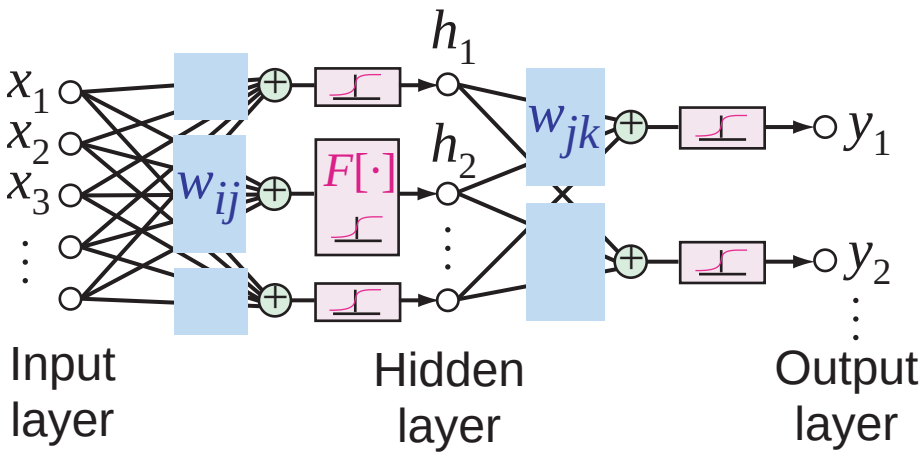
- **Linear functions give linear boundaries**
  - planes and hyperplanes as dimensions increase
- **Linear boundaries can become curves under feature transformations**
  - e.g. a linear discriminant in $\boldsymbol{x}' = [x_1^2\ x_2^2\ ...]^T$
- **What about more complex boundaries?**
  - i.e. if a linear discriminant is $\sum w_i x_i$ how about a nonlinear function?
  - $F[\sum w_i x_i]$ changes only threshold space, but $\sum_j F[\sum_i w_{ij} x_i]$ offers more flexibility, and $F[\sum_j w_{jk} \cdot F[\sum_i w_{ij} x_i]]$ has even more ...



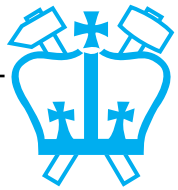
Neural networks

- **Sums over nonlinear functions of sums → large range of decision surfaces**
- **e.g. Multi-layer perceptron (MLP) with 1 hidden layer:**

$$y_k = F[\sum_j w_{jk} \cdot F[\sum_j w_{ij} x_i]]$$



- **Problem is finding the weights w_{ij} ... (*training*)**



Back-propagation training

- **Find w_{ij} to minimize e.g. $E = \sum_n \left| y(x_n) - t_n \right|^2$ for training set of patterns $\{x_n\}$ and desired (target) outputs $\{t_n\}$**
- **Differentiate error with respect to weights**
  - contribution from each pattern x_n, t_n:

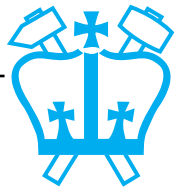
$$y_k = F[\sum_j w_{jk} \cdot h_j]$$

$$\frac{\partial E}{\partial w_{jk}} = \frac{\partial E}{\partial y} \cdot \frac{\partial y}{\partial \Sigma} \cdot \frac{\partial}{\partial w_{jk}} (\sum_j w_{jk} h_j)$$

$$= 2(y - t) \cdot F'[\Sigma] \cdot h_j$$

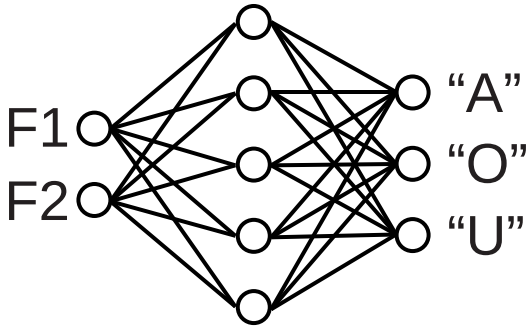
$$w_{jk} = w_{jk} - \alpha \cdot \frac{\partial E}{\partial w_{jk}}$$

- **i.e. gradient descent with learning rate α**



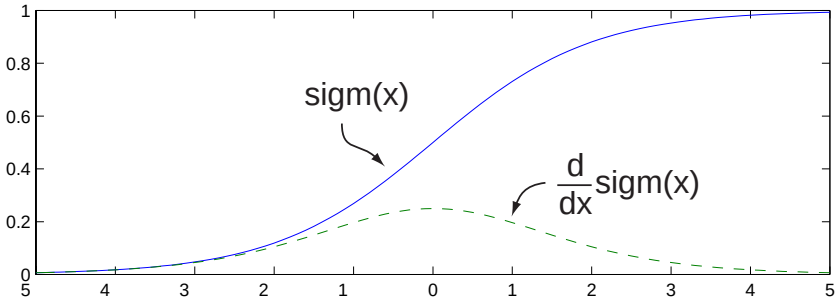
Neural net example

- **2 input units (normalized F1, F2)**
- **5 hidden units, 3 output units (“U”, “O”, “A”)**

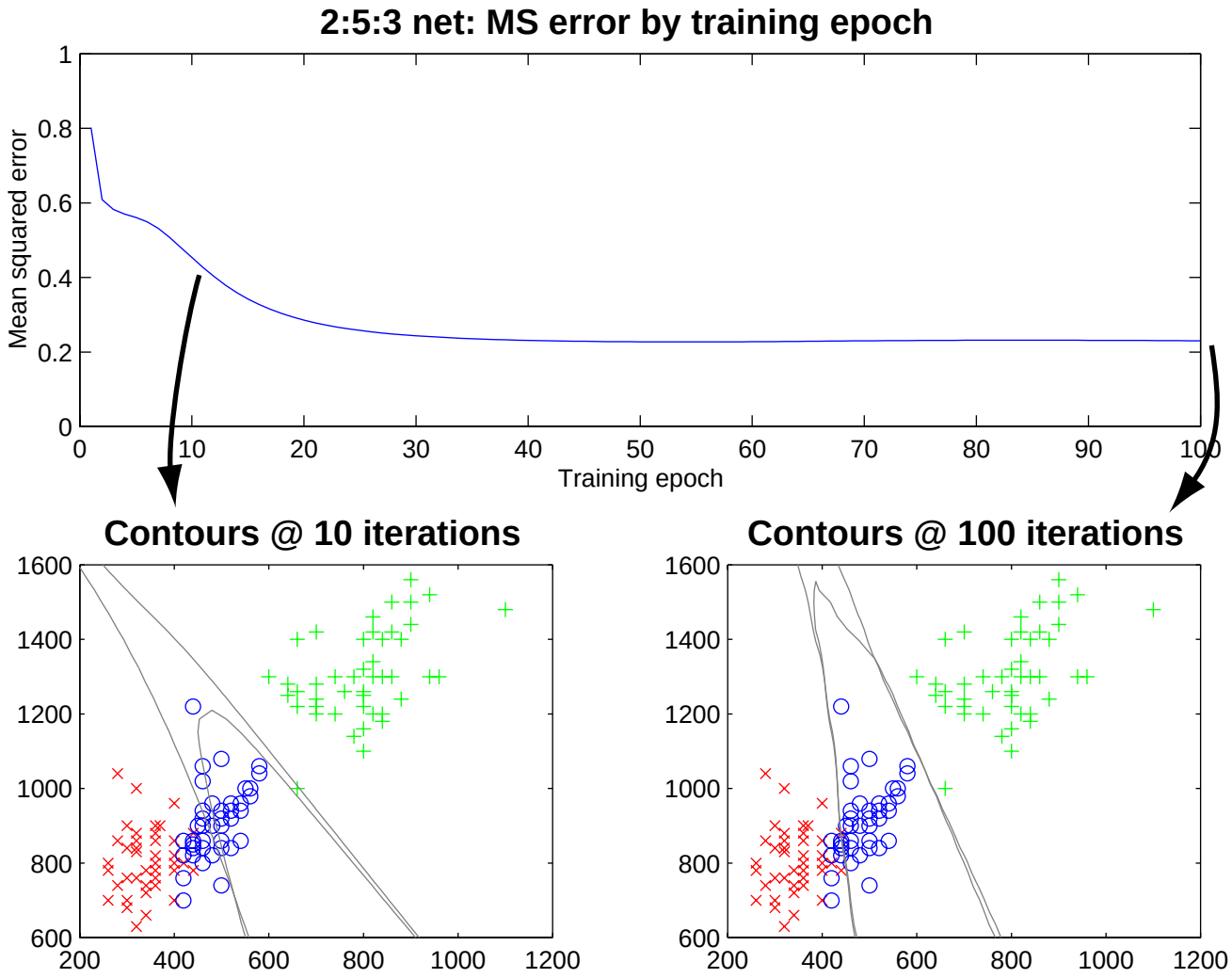


- **Sigmoid nonlinearity:**

$$F[x] = \frac{1}{1+e^{-x}} \quad \Rightarrow \quad \frac{dF}{dx} = F(1-F)$$



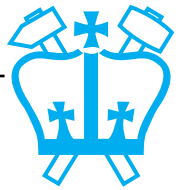
Neural net training



example...

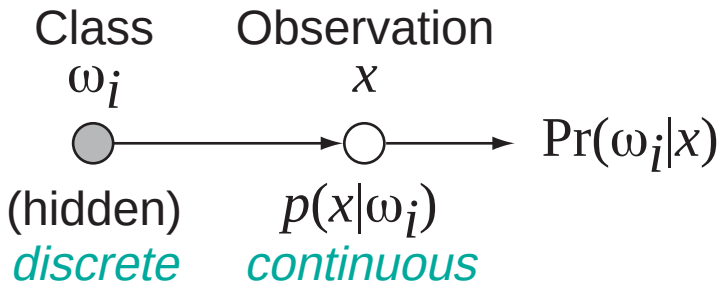
Outline

1. Music Content Analysis
2. Pattern Classification
3. **The Statistical Approach**
   - Conditional distributions
   - Bayes rule
4. Distribution Models
5. Singing Detection

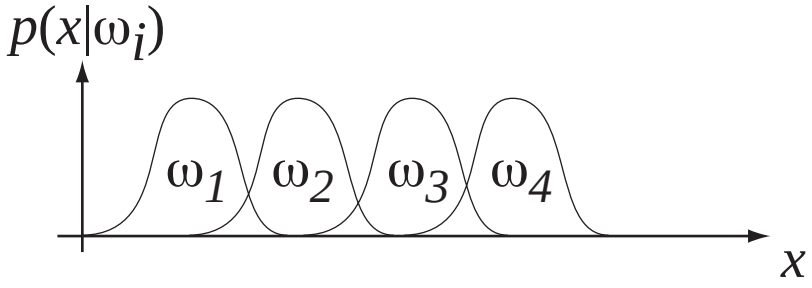


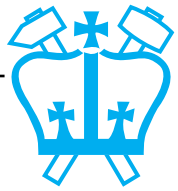
3 The Statistical Approach

- **Observations are random variables whose distribution depends on the class:**



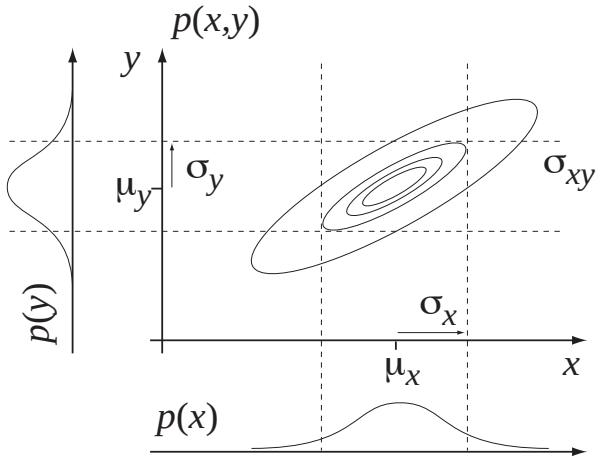
- **Source distributions** $p(x|\omega_i)$
  - reflect variability in feature
  - reflect noise in observation
  - generally have to be estimated from data (rather than known in advance)





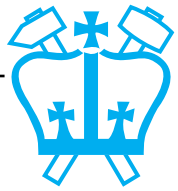
Random Variables review

- **Random vars have joint distributions (pdf's):**



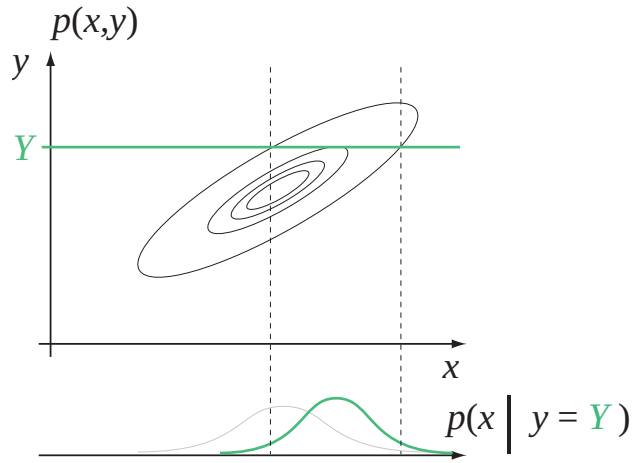
- marginal $p(x) = \int p(x, y)dy$

- covariance $\Sigma = E[(\mathbf{o} - \mu)(\mathbf{o} - \mu)^T] = \begin{bmatrix} \sigma_x^2 & \sigma_{xy} \\ \sigma_{xy} & \sigma_y^2 \end{bmatrix}$



Conditional probability

- **Knowing one value in a joint distribution constrains the remainder:**

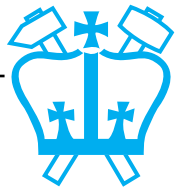


- **Bayes' rule:** $p(x, y) = p(x|y) \cdot p(y)$

$$\Rightarrow p(y|x) = \frac{p(x|y) \cdot p(y)}{p(x)}$$

→ **can reverse conditioning given priors/marginal**

- either term can be discrete or continuous



Priors and posteriors

- **Bayesian inference can be interpreted as updating prior beliefs with new information, x:**

Bayes' Rule:

Likelihood

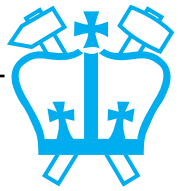
$$Pr(\omega_i) \cdot \frac{p(x|\omega_i)}{\sum_j p(x|\omega_j) \cdot Pr(\omega_j)} = Pr(\omega_i|x)$$

Prior probability

'Evidence' = p(x)

Posterior probability

- **Posterior is prior scaled by likelihood & normalized by evidence (so Σ(posteriors) = 1)**
- **Objection: priors are often unknown**
  - but omitting them amounts to assuming they are all equal



Bayesian (MAP) classifier

- **Minimize the probability of error by choosing *maximum a posteriori* (MAP) class:**

$$\hat{\omega} = \underset{\omega_i}{\operatorname{argmax}} \, Pr(\omega_i | x)$$

- **Intuitively right - choose most probable class in light of the observation**

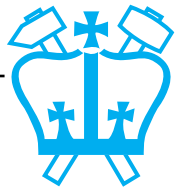
- **Given models for each distribution $p(x|\omega_i)$,**

  the search for $\hat{\omega} = \underset{\omega_i}{\operatorname{argmax}} \, Pr(\omega_i | x)$

  becomes $\underset{\omega_i}{\operatorname{argmax}} \, \dfrac{p(x|\omega_i) \cdot Pr(\omega_i)}{\sum_j p(x|\omega_j) \cdot Pr(\omega_j)}$

  but denominator = $p(x)$ **is the same over all** ω_i

  hence $\hat{\omega} = \underset{\omega_i}{\operatorname{argmax}} \, p(x|\omega_i) \cdot Pr(\omega_i)$



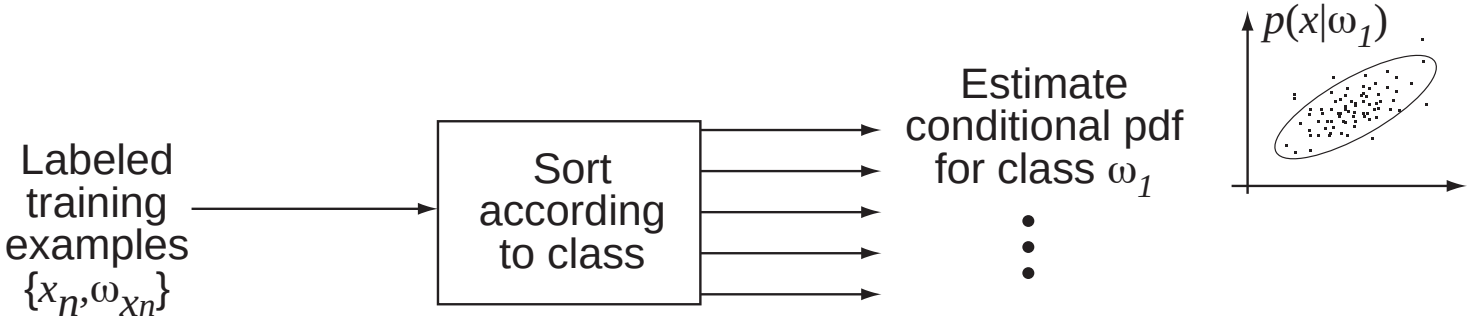
Practical implementation

- **Optimal classifier is** $\hat{\omega} = \underset{\omega_i}{\operatorname{argmax}} Pr(\omega_i|x)$

  but we don't know $Pr(\omega_i|x)$

- **Can model directly e.g. train a neural net to map from inputs** x **to a set of outputs** $Pr(\omega_i)$ **- a *discriminative* model**

- **Often easier to model conditional distributions** $p(x|\omega_i)$ **then use Bayes' rule to find MAP class**



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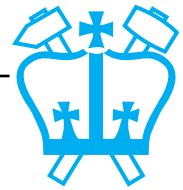
   - Gaussian models
   - Gaussian mixtures
5. Singing Detection



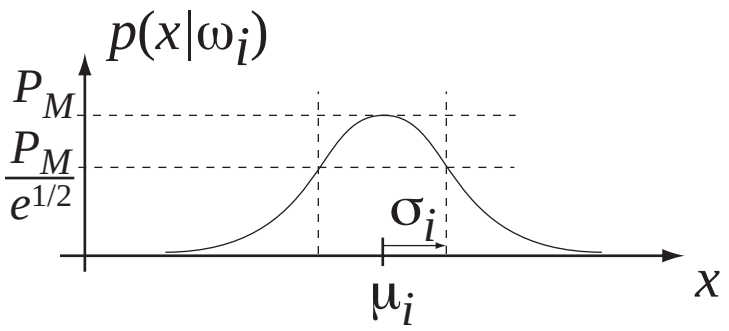
4 Distribution Models

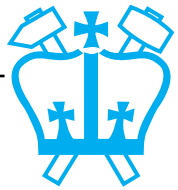
- **Easiest way to model distributions is via parametric model**
  - assume known form, estimate a few parameters
- **Gaussian model is simple & useful:**

in 1 dim: $p(x|\omega_i) = \frac{1}{\sqrt{2\pi}\sigma_i} \cdot \exp\left[-\frac{1}{2}\left(\frac{x-\mu_i}{\sigma_i}\right)^2\right]$

normalization to make it sum to 1

- **Parameters mean μ_i and variance σ_i^2 → fit**

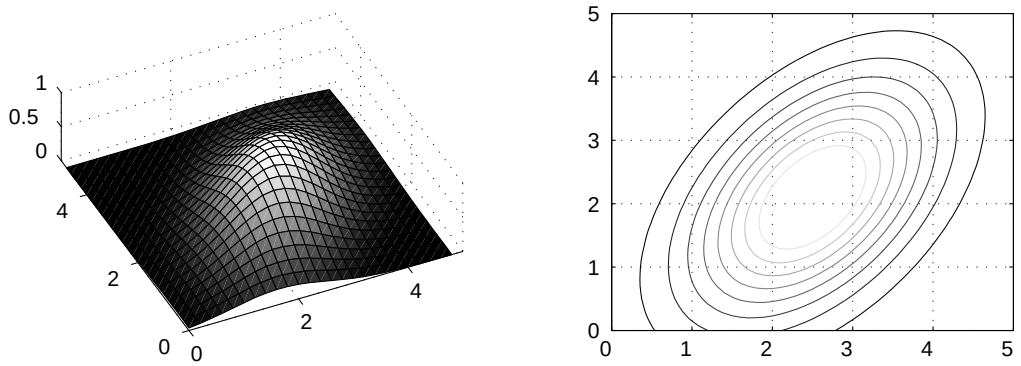




Gaussians in *d* dimensions:

$$p(\mathbf{x}|\omega_i) = \frac{1}{(\sqrt{2\pi})^d |\Sigma_i|^{1/2}} \cdot \exp\left[-\frac{1}{2}(\mathbf{x}-\boldsymbol{\mu}_i)^T \Sigma_i^{-1}(\mathbf{x}-\mu_i)\right]$$

- **Described by d dimensional mean vector μ_i and d x d covariance matrix Σ_i**



- **Classify by maximizing log likelihood i.e.**

$$\underset{\omega_i}{\text{argmax}} \left[-\frac{1}{2}(\mathbf{x}-\boldsymbol{\mu}_i)^T \Sigma_i^{-1}(\mathbf{x}-\mu_i) - \frac{1}{2}\log|\Sigma_i| + \log Pr(\omega_i)\right]$$

Gaussian Mixture models (GMMs)

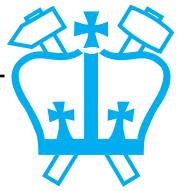
- **Single Gaussians *cannot* model**
  - distributions with multiple modes
  - distributions with nonlinear correlation
- **What about a weighted sum?**

  i.e. $p(x) \approx \sum_k c_k p(x|m_k)$

  where {c_k} is a set of weights and

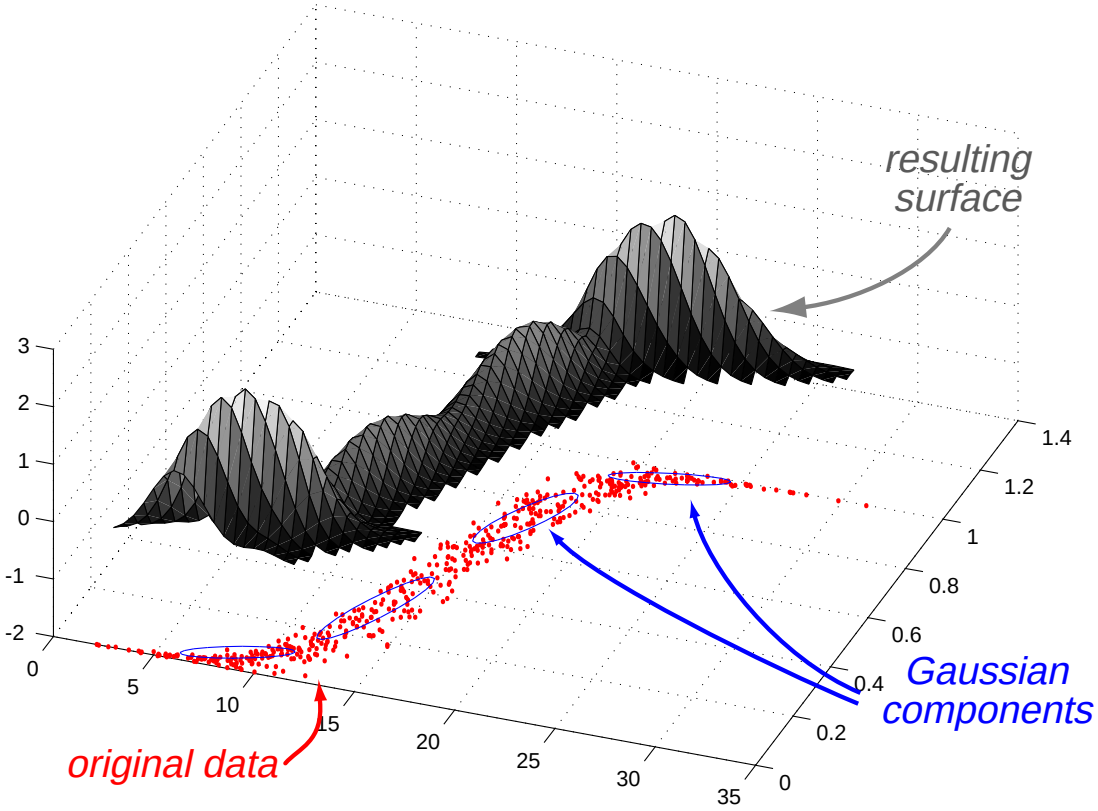
  {$p(x|m_k)$} is a set of Gaussian components

  - can fit anything given enough components
- **Interpretation: each observation is generated by one of the Gaussians, chosen at random with priors** $c_k = Pr(m_k)$

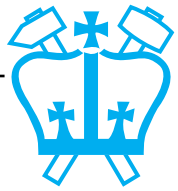


Gaussian mixtures (2)

- **e.g. nonlinear correlation:**



- **Problem: finding c_k and m_k parameters**
  - easy if we knew *which* m_k generated each x

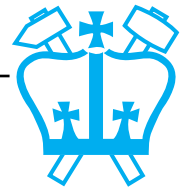


Expectation-maximization (EM)

- **General procedure for estimating a model when some parameters are unknown**
  - e.g. which component generated a value in a Gaussian mixture model
- **Procedure:**
  Iteratively update fixed model parameters Θ to maximize Q=expected value of log-probability of known training data x_{trn}
  and unknown parameters u:

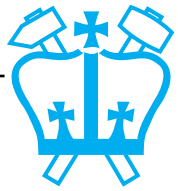
$$Q(\Theta, \Theta_{old}) = \sum_u Pr(u|x_{trn}, \Theta_{old}) \log p(u, x_{trn}|\Theta)$$

  - iterative because $Pr(u|x_{trn}, \Theta_{old})$ changes each time we change Θ
  - can prove this increases data likelihood, hence maximum-likelihood (ML) model
  - *local* optimum - depends on initialization



Fitting GMMs with EM

- **Want to find component Gaussians $m_k = \{\mu_k, \Sigma_k\}$ plus weights $c_k = Pr(m_k)$ to maximize likelihood of training data x_{trn}**
- **If we could assign each x to a particular m_k, estimation would be direct**
- **Hence, treat ks (mixture indices) as unknown, form $Q = E[\log p(x, k|\Theta)]$, differentiate with respect to model parameters → equations for μ_k, Σ_k and c_k to maximize Q...**



GMM EM update equations:

- **Solve for maximizing Q:**

$$\mu_k = \frac{\sum_n p(k|x_n, \Theta) \cdot x_n}{\sum_n p(k|x_n, \Theta)}$$

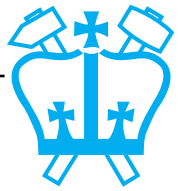
$$\Sigma_k = \frac{\sum_n p(k|x_n, \Theta)(x_n - \mu_k)(x_n - \mu_k)^T}{\sum_n p(k|x_n, \Theta)}$$

$$c_k = \frac{1}{N}\sum_n p(k|x_n, \Theta)$$

- **Each involves $p(k|x_n, \Theta)$,**

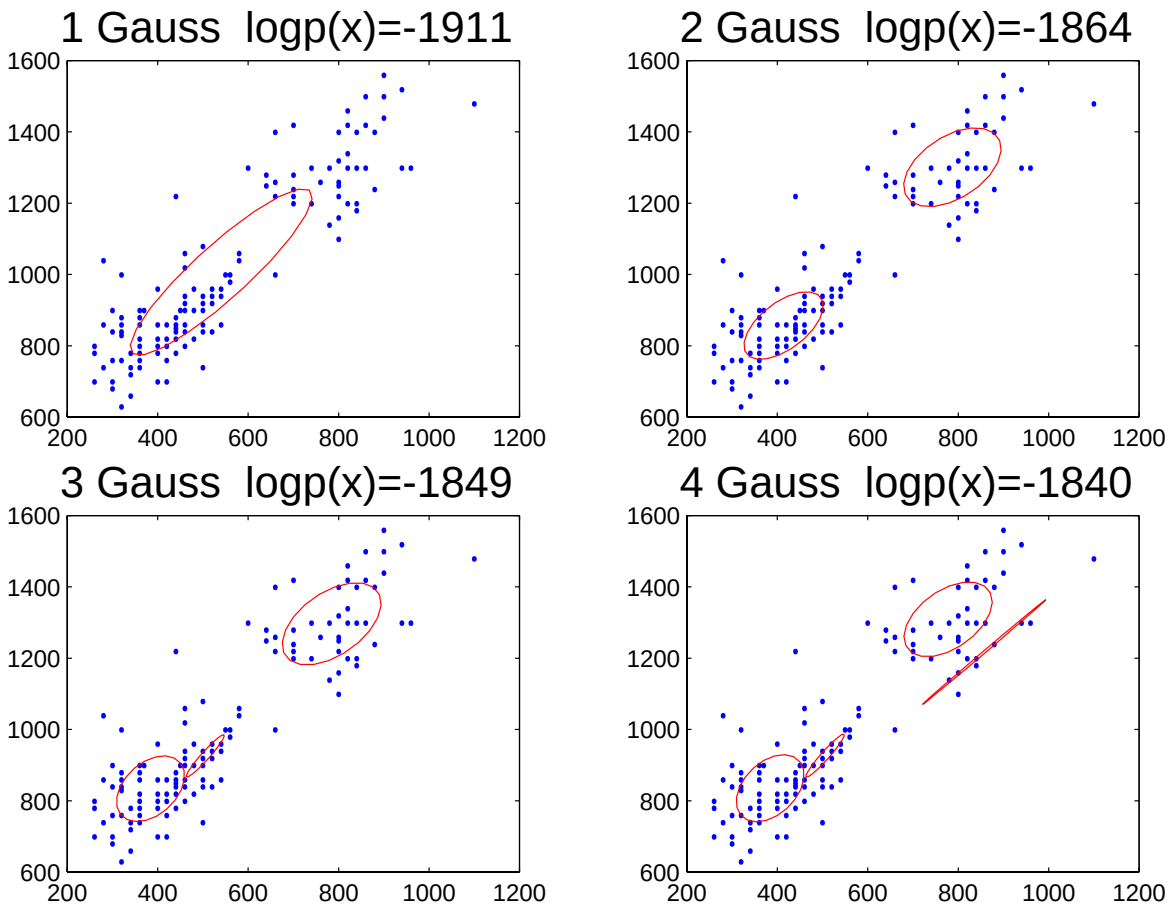
  'fuzzy membership' of x_n to Gaussian k

- **Parameter is just sample average, weighted by 'fuzzy membership'**



GMM examples

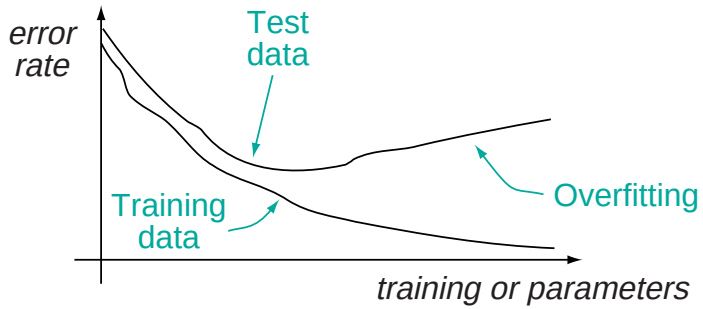
- **Vowel data fit with different mixture counts:**



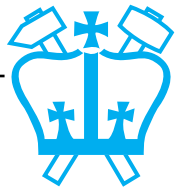
example...

Methodological Remarks: Training and test data

- **A rich model can learn *every* training example (*overtraining*)**

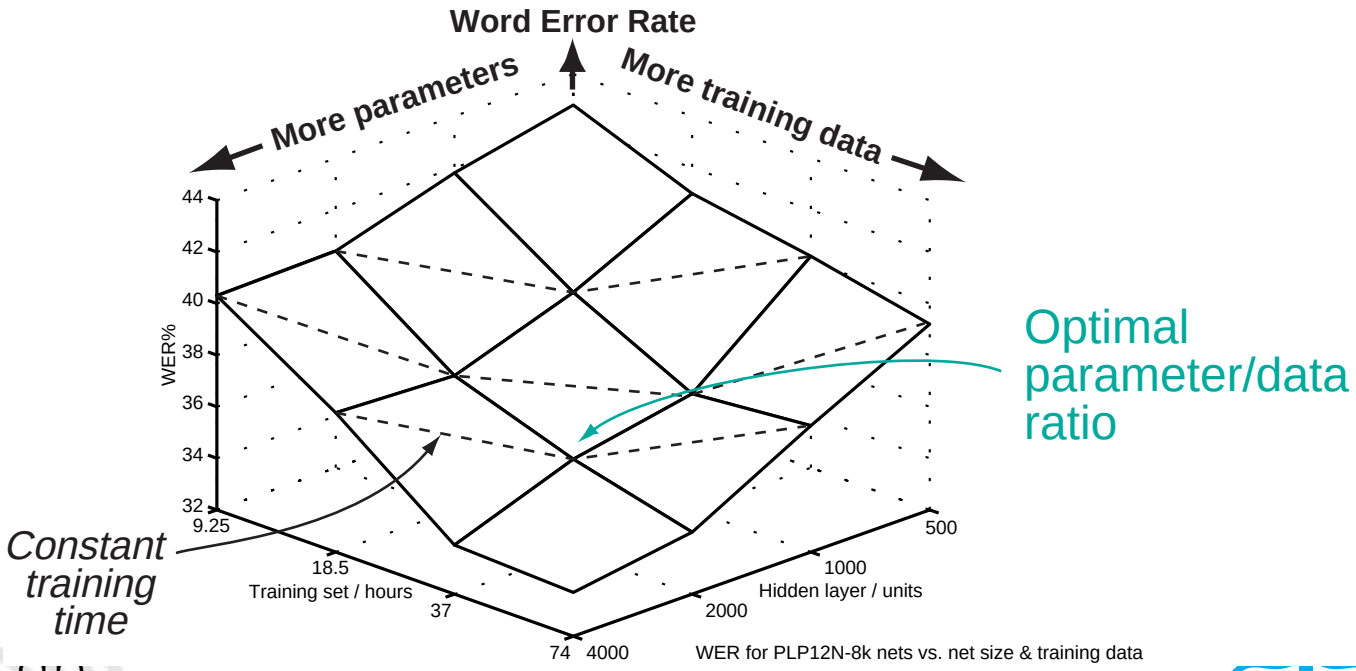


- **But, goal is to classify new, unseen data i.e. *generalization***
  - sometimes use 'cross validation' set to decide when to stop training
- **For evaluation results to be meaningful:**
  - don't test with training data!
  - don't *train* on *test* data (even indirectly...)



Model complexity

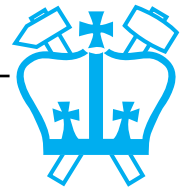
- **More model parameters → better fit**
  - more Gaussian mixture components
  - more MLP hidden units
- **More training data → can use larger models**
- **For best generalization (no overfitting), there will be some optimal model size:**



WER for PLP12N-8k nets vs. net size & training data

Outline

1. Music Content Analysis
2. Pattern Classification
3. The Statistical Approach
4. Distribution Models
5. **Singing Detection**
   - Motivation
   - Features
   - Classifiers

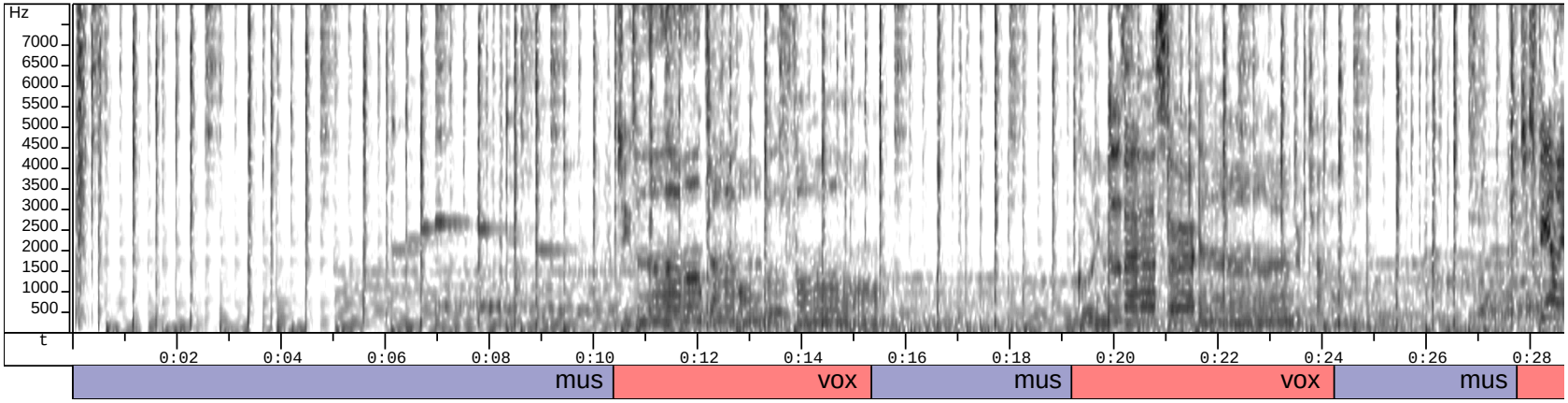


5 Singing Detection

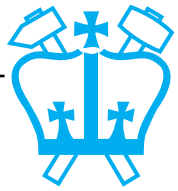
(Berenzweig et al. ’01)

- **Can we automatically detect when singing is present?**

File: /Users/dpwe/projects/aclass/aimee.wav

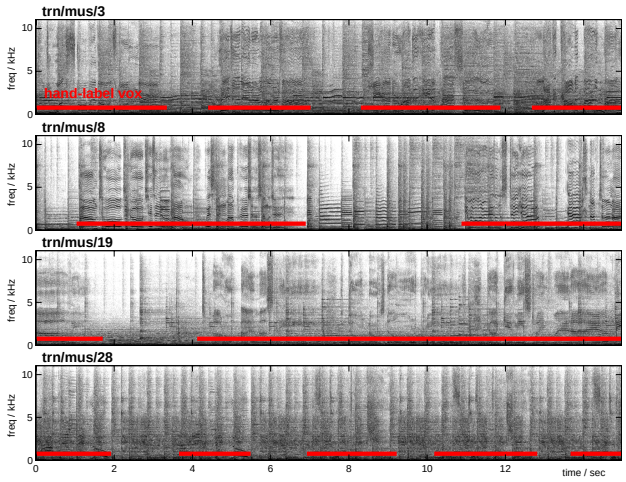


- for further processing (lyrics recognition?)
- as a song signature?
- as a basis for classification?



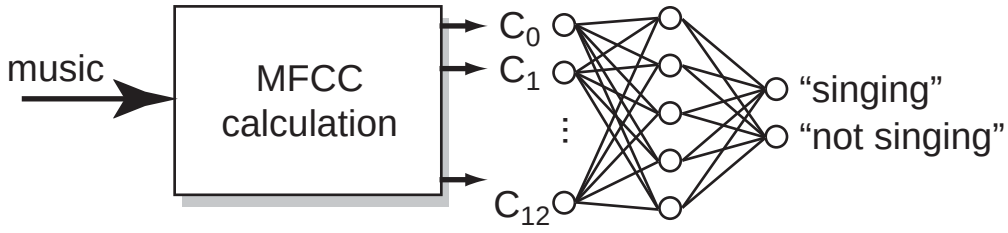
Singing Detection: Requirements

- **Labelled training examples**
  - 60 x 15 sec. radio excerpts
  - hand-mark sung phrases
- **Labelled test data**
  - several complete tracks from CDs, hand-labelled
- **Feature choice**
  - Mel-frequency Cepstral Coefficients (MFCCs) popular for speech; maybe sung voice too?
  - separation of voices?
  - temporal dimension
- **Classifier choice**
  - MLP Neural Net
  - GMMs for singing / music
  - SVM?

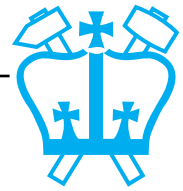


MLP Neural Net

- **Directly estimate** $p(\text{singing} \mid x)$

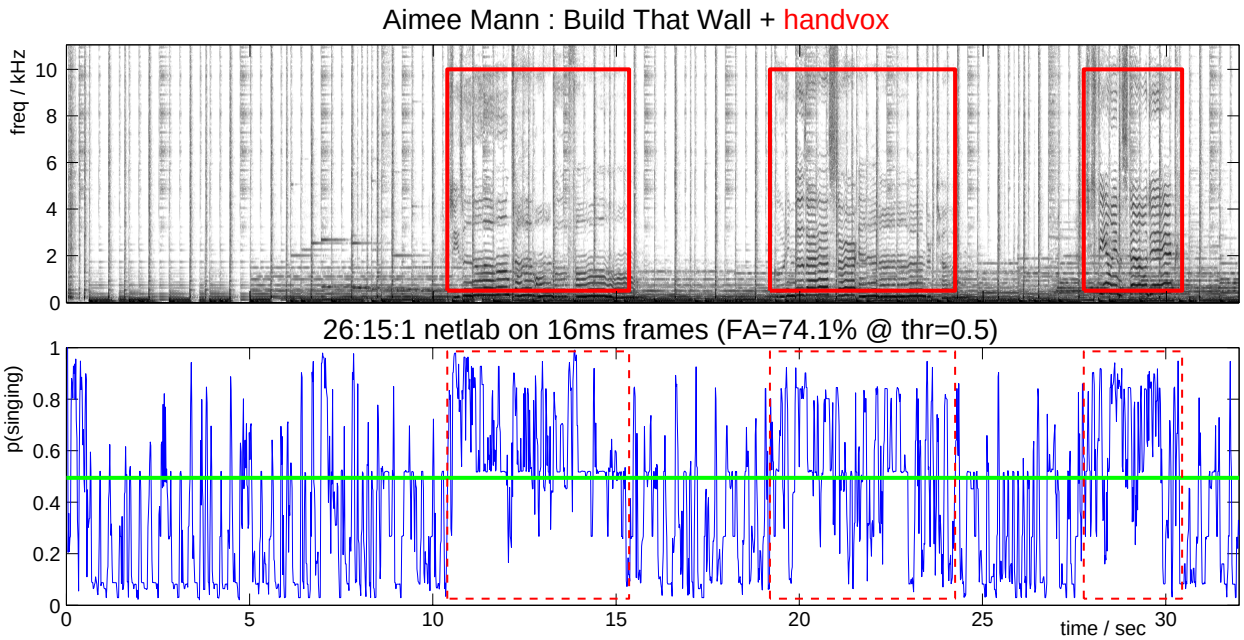


  - net has 26 inputs (+Δ), 15 HUs, 2 o/ps (26:15:2)
- **How many hidden units?**
  - depends on data amount, boundary complexity
- **Feature context window?**
  - useful in speech
- **Delta features?**
  - useful in speech
- **Training parameters...**

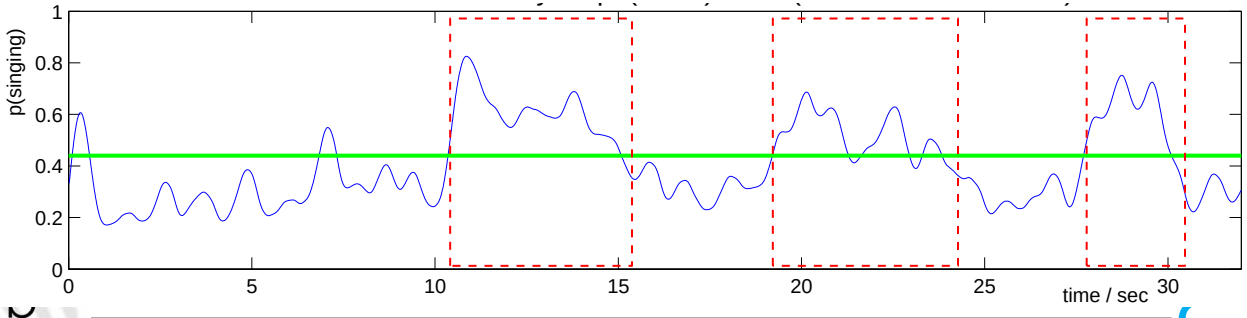


MLP Results

- **Raw net outputs on a CD track (FA 74.1%):**

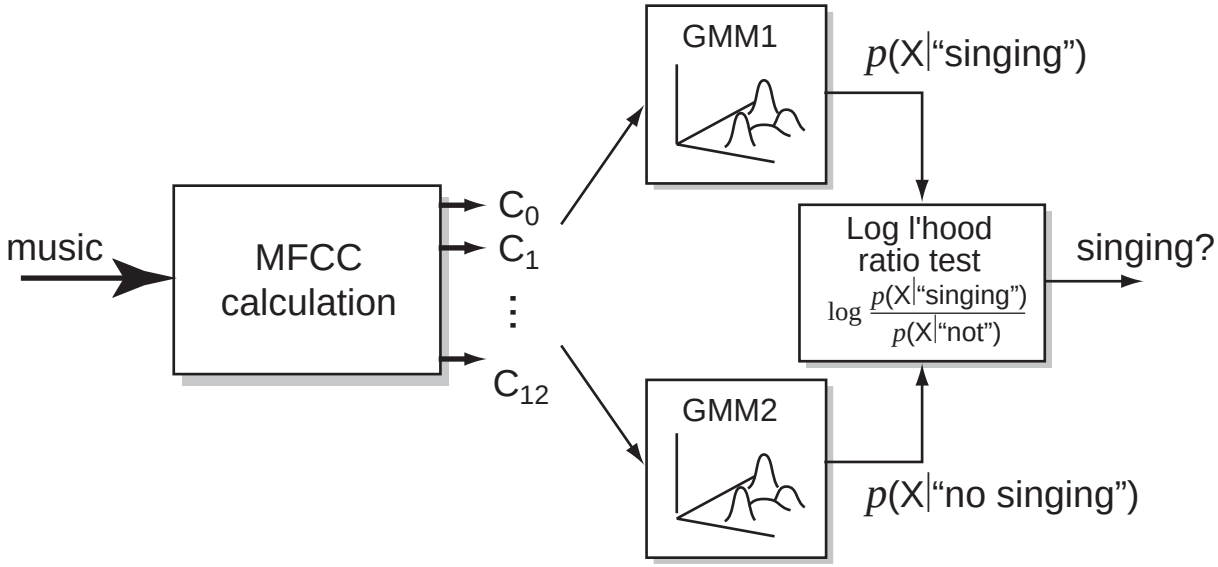


- **Smoothed for continuity: best FA = 90.5%**



GMM System

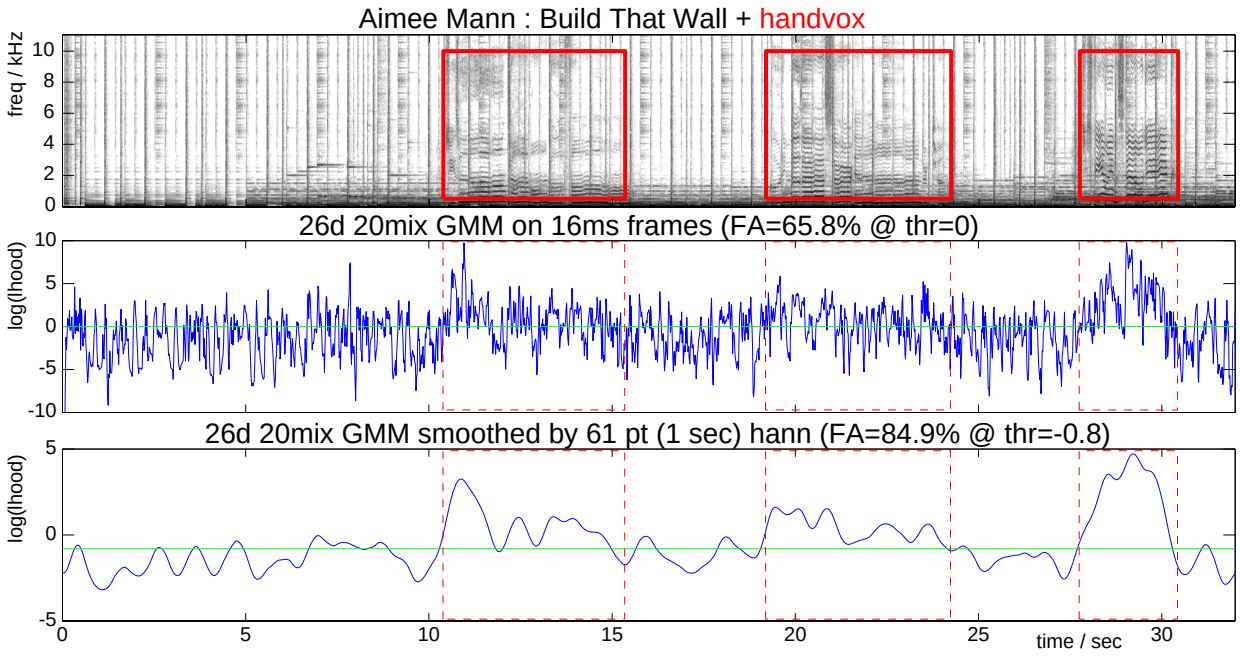
- **Separate models for $p(x|sing)$, $p(x|no\ sing)$**
  - combined via likelihood ratio test



- **How many Gaussians for each?**
  - say 20; depends on data & complexity
- **What kind of covariance?**
  - diagonal (spherical?)

GMM Results

- **Raw and smoothed results (Best FA=84.9%):**

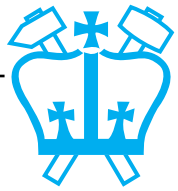


- **MLP has advantage of discriminant training**
- **Each GMM trains only on data subset**
  → faster to train? (2 x 10 min vs. 20 min)

Summary

- **Music content analysis: Pattern classification**
- **Basic machine learning methods: Neural Nets, GMMs**
- **Singing detection: classic application**

but... the time dimension?



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